

**Manuscript version: Author's Accepted Manuscript**

The version presented in WRAP is the author's accepted manuscript and may differ from the published version or Version of Record.

**Persistent WRAP URL:**

<http://wrap.warwick.ac.uk/123685>

**How to cite:**

Please refer to published version for the most recent bibliographic citation information. If a published version is known of, the repository item page linked to above, will contain details on accessing it.

**Copyright and reuse:**

The Warwick Research Archive Portal (WRAP) makes this work by researchers of the University of Warwick available open access under the following conditions.

© 2019 Elsevier. Licensed under the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

**Publisher's statement:**

Please refer to the repository item page, publisher's statement section, for further information.

For more information, please contact the WRAP Team at: [wrap@warwick.ac.uk](mailto:wrap@warwick.ac.uk).

# Does your neighbour know you better?

## The supportive role of local banks in the financial crisis

**Abstract.** Relationship lending allows local banks to collect private information about their customers and to mitigate information asymmetries that often lead to credit rationing. In this paper, we argue that soft information collected through relationship lending favors lending decisions even when borrowers' quality is poor from a "hard-information" perspective. We compare the behavior of local versus non-local banks using data immediately before and after the 2007-08 Financial Crisis. We exploit the heterogeneity in banks' reliance on soft information to study how their lending strategies changed when firms' hard-information indicators deteriorated after the outbreak of the financial crisis. Our paper shows that firms predominantly funded by local banks reported lower credit rationing immediately after the outbreak of the 2007-08 Financial Crisis. In the same period local banks were also less likely to terminate existing relationships with their customers, suggesting that they continued funding their clients even when borrowers' balance sheet variables worsened. We rule out alternative hypotheses explaining our results, such as demand effects, "zombie-lending" behavior, or different impacts the financial crisis had on the credit supply of local versus local firms. This leads us to conclude that thanks to their greater reliance on soft information, local lenders supported their customers to a higher extent during bad times, at least in the period following immediately the outbreak of the Financial Crisis.

**JEL Classification:** G21, G30, F34.

**Key Words:** Local Banks, Soft Information, Relationship Lending, Financial Crisis, Credit Rationing

## 1. Introduction

Local banks play a crucial role in funding small and opaque businesses. A number of studies have shown that the geographical proximity between banks and firms affects the way information is processed and collected and, in turn, how credit is made available (e.g. Petersen and Rajan, 2002; Stein, 2005). The personal relationship local bankers establish with funded entrepreneurs – known in the literature as “relationship lending” – allows lenders to acquire private, “soft” information from their clients. This relates, among others, to the quality of borrowers’ managerial practices, their relationships with suppliers and customers, and their impact on the local economy (Berger, 1999; Berger and Udell, 2002; Petersen, 2004).

Owning soft information helps lenders mitigate information asymmetries in credit markets, which often lead to credit rationing, as shown in the seminal paper by Stiglitz and Weiss (1981). Thanks to soft information, small and opaque firms are able to receive funding even in absence of public, “hard” information (e.g. Berger and Udell, 1995; DeYoung et al., 2004).

Against this background, a related question is which role soft information plays when hard information exists, but it suggests that borrowers have poor quality. In particular, how do banks take their lending decisions when borrowers’ hard-information credit assessment suddenly becomes discouraging? Findings from this paper that soft information can lead local lenders to grant credit when hard information would suggest the opposite.

Since local banks establish closer relationships with their borrowers, in principle they can collect more accurate information upon perspective customers. It follows that local banks might grant credit when soft information reveals that the borrower’s quality is good, despite the firm’s “hard-information” profile might look poor. In such cases soft information may work as a substitute for hard information in lending decisions.

On the contrary, non-local lenders build their lending decisions mostly on hard information. As a consequence, if the borrower’s “hard-information” quality is not satisfactory, these banks might deny credit without resorting to soft information to validate – or change – such assessment.

We test these predictions using a novel dataset of loans granted by 348 Italian banks to a representative sample of 2,373 Italian firms in the years 2007 and 2008. This period coincides with the year immediately before and after the collapse of Lehman Brothers, which took place in September 2008. These data allow us to distinguish between local and non-local banks and to relate banks’ lending strategies to banks’ characteristics – and to those of their borrowers – before and after the financial crisis.

Our identification strategy exploits the heterogeneity in banks’ reliance on relationship lending to study the lending strategies of local versus non-local banks before and after the outburst of the 2007-08 Financial Crisis. It builds on two assumptions: first, local banks use soft information to a higher extent than non-local banks (e.g. Agarwal and Hauswald, 2010), but they rely on hard information to a similar extent. One reason for this is that local banks tend to be more geographically concentrated – also because of regulatory issues – and, as such, they can specialize to a greater extent – and therefore collect more accurate information – on the firms that are located in the local credit markets they operate in.

Second, firms’ hard-information indicators became unexpectedly worse in the period immediately after the outbreak of the financial crisis – but not necessarily their soft-information profile.<sup>1</sup> In order to account for credit demand, we only select and include in the analysis firms that borrowed from both local and non-local banks, the year before the crisis. This allows us to control for any potential selection effect in the pool of firms funded by local versus non-local banks, and to

---

<sup>1</sup> We will discuss extensively how firms’ balance sheet worsened after the financial crisis spread in Section 5.1.

neutralize any differential impact the financial crisis had on firms relying on local versus non-local credit.<sup>2</sup>

Our hypothesis is that despite firms' hard-information outlook was negatively affected by the outburst of the financial crisis, local banks were able to identify and fund creditworthy firms through their soft-information "screening". Thus, any difference in lending across local and non-local banks to the *same* set of firms, once firms' hard-information indicators deteriorated in 2008, should be precisely driven by banks' different reliance and use of relationship lending. This would be true unless the financial crisis hit local and non-local banks in a different way – which we find not being the case.

In line with our predictions, our main finding is that firms borrowing from local banks reported lower rates of credit rationing in 2008 than firms borrowing from non-local banks. This result is robust after controlling for the characteristics of the bank-firm relationship, banks' balance sheet variables, as well as firms' characteristics. It also holds after controlling for a set of location-size-age-industry Fixed Effects (in a similar spirit as Degryse et al., 2018), suggesting that firms' "unobservable" traits – those that can only be captured through relationship lending – play a significant role in explaining lenders' supply decisions.

To explore the mechanism underlying this result, we look at the extensive margin of credit and find that local banks were less likely than non-local banks to terminate existing relationships with their customers during the financial crisis. Conditional on a relationship being already in place when hard-information indicators were good, local banks were less likely to cut such relationship as hard-information indicators became poorer. This suggests that local banks were able to leverage on soft information to identify good customers.

Taken together, our findings show that relationship lending plays a crucial role in banks' lending decisions. Thanks to soft information, local banks kept funding their customers to a higher

---

<sup>2</sup> We thank an anonymous referee for pointing this out.

extent than non-local lenders when hard-information indicators suddenly worsened. Two *caveats* to our results should however be mentioned. First, to precisely account for the role of hard versus soft information, we only look at the evolution of firm-bank relationships conditional on them being already in place before the outbreak of the 2007-08 Financial Crisis, when hard-information indicators were still satisfactory. On the contrary, we cannot speak to changes in banks' lending decisions – and to the role of soft information – towards firms whose hard-information outlook had always been unsatisfactory. Second, ours can be considered as short-term findings – we indeed study loan outcomes and firms' financial constraints only in the year before and after the collapse of Lehman Brothers. We cannot speak to how longer-term, real effects of the financial crisis – for instance, differential impact of the shock on tradable versus non-tradable sectors – may affect firms' probability to report being credit rationed in later years.

To complete our analysis, we rule out competing hypotheses that might explain our results. In fact, a natural question is whether our findings are driven by local lenders adopting a “zombie lending” strategy (Peek and Rosengren, 2005; Albertazzi and Marchetti, 2010), rather than funding creditworthy customers identified through soft information. Under this view, local banks, which are usually small in size and also less capitalized, might have kept lending to firms they had high credit exposure to even during financial crises. This is in order to avoid that such firms, once in financial distress, may have compromised the banks' stability. If this were the case, we should observe local banks to be less likely to terminate existing relationships with firms with worse balance sheet characteristics or with firms holding relatively high credit shares during the financial crisis. This hypothesis is however not confirmed in the data. In addition, one may wonder whether our results are driven by a different impact of the financial shock on local versus non-local banks, rather than by differences in lenders' reliance on soft information.

Because of their nature, local banks might have been subject to less strict regulatory requirements during the financial crisis, thus generating differences in the liquidity provision of local versus non-local banks. We study the intensive margin of credit and we find that local and

non-local banks did not differently experience credit contraction resulting from the 2007-08 Financial Crisis.

All in all, our results show that local lenders, who make larger use of soft information through relationship lending, tightened their credit supply to a lower extent than non-local banks in 2008. They did so especially when hard-information revealed a poorer firms' outlook. Our findings suggest that soft-information can substitute hard information, and can help lenders make better-informed lending decisions. When it is used, as it is the case for local banks, firms experience greater credit stability, at least in the short-term, even in periods when their balance sheet characteristics significantly worsened.

Our paper contributes to the literature on soft information and local banks, along several dimensions. First, it focuses on the role of relationship lending, in a similar spirit as Liberti (2003; 2005) and of Liberti and Mian (2009). Second, it looks at the importance of soft information for small business funding, particularly in periods of financial downturns. For instance, Gobbi and Sette (2013) show that, after Lehman Brothers' default, firms benefited from closer bank lending relationships, both in terms of credit growth and interest rates. In a similar spirit, Gambacorta and Mistrulli (2011) document that close lending relationships were effective in insulating firms from the financial crisis as their borrowing costs increased less than those of other firms. Presbitero et al. (2014) find that in credit markets with a stronger presence of functionally close banks, large, good-quality firms have experienced less credit tightening than in functionally distant credit markets.

Our paper also contributes to the literature that studies how to identify and measure soft information. Garcia-Appendini (2011) takes an "indirect" approach and shows that banks rely to a lower extent on public credit registries when they have access to soft information. In a similar spirit, Cerqueiro, Degryse and Ongena (2010) look at residuals in regressions with public credit information to quantify soft information.

Finally, from a policy perspective, our results highlight the importance of local banks for small business funding, even during financial turmoils, as they prove to be important buffers against negative shocks for firms.

The paper is organized as follows: Section 2 discusses the theoretical framework our identification strategy builds on. Section 3 focuses on local banks and their characteristics; in Section 4 we present the data and descriptive statistics. In Section 5 we illustrate results from our analysis. Robustness checks are discussed in Section 6. Section 7 concludes.

## 2. Testable Predictions

One of the core differences between local and non-local banks lies in their geographical concentration: local banks have a more limited geographical outreach and, as such, a smaller loan and customer portfolio.<sup>3</sup> Non-local banks, on the contrary, can operate in a larger set of credit markets. It follows that, compared to non-local banks, local banks can only cater to a smaller set of firms – those that are located in the same credit markets they operate. Therefore, they will exclusively focus on lending to such firms, precisely because these firms represent the entire pool of (potential) customers. This results into a geographical segmentation of credit markets, wherein local banks specialise on certain firms – and possibly on certain industry sectors, depending also on the specific local credit market – while non-local banks can diversify their client and lending portfolio to a higher extent across different markets.<sup>4</sup>

This geographical segmentation results into different lending-technology specializations of banks. By focusing on the local economy, local banks are able to collect private, soft information

---

<sup>3</sup> This is mostly due to regulatory issues. Credit Cooperative Banks and (some) Savings Bank are subject to territorial constraints, see for instance: [http://www.creditoperativo.it/template/default.asp?i\\_menuID=35356](http://www.creditoperativo.it/template/default.asp?i_menuID=35356). A translation of this page is available upon request.

<sup>4</sup> In fact, if we look to our data, we find that local banks operate on average in 2 local credit markets, vis-à-vis 30 for non-local banks.



to a greater extent.<sup>5</sup> Soft information has thus more weight in lending decisions for local banks than for non-local ones.

At the same time, the extent to which both types of banks collect and process hard information – like firms’ balance sheets, financial statements, and credit registries – should be similar across banks.

We make the hypothesis that in normal times, when firm’ hard-information indicators are not affected by financial shocks, hard information and soft information provide a similar assessment of a firm’s quality. In fact, it is reasonable to think that if the firm has high productivity, rarely the management practices adopted are bad.

During financial shocks however – or at least in the period immediately following the outbreak of a financial crisis – hard information worsens, but not necessarily soft information worsens, too. This is especially true when the causes of hard-information deterioration are not firm-specific, but rather systemic, as it was during the 2007-08 Financial Crisis.<sup>6</sup>

This implies that local banks can potentially have a larger set of information to use in making lending decisions. And when hard information worsens, they might still keep lending to firms in their local community proving that private information is promising.

In light of this discussion, we make the following testable prediction:

---

<sup>5</sup> There are many reasons why this could be the case: first, the branch network of local banks is concentrated only in certain areas/markets thus facilitating interactions with customers and the consequent collection of private information; second, the distance between the bank’s headquarter and branches is smaller, thus information between different layers of the banking institutions can be exchanged faster (see among others Alessandrini et al., 2009). There is also plenty of anecdotal evidence on the behavior of managers and customers of local banks (in particular of Credit Cooperative Banks).

<sup>6</sup> For instance, while firms’ productivity or employment can significantly worsen during financial downturns, it is hard to imagine that an entrepreneur would adopt worse managerial practices, or that cultural norms would change during financial crises.

**Prediction:** *As the quality of a firm worsens, only banks that rely on soft information will keep lending to this firm, as long as soft information reveals that the firm's quality is good.*

In order to test this Prediction, we consider the universe of loans that a panel of 2,373 Italian firms received from 348 Italian banks in 2007 and 2008 and study whether firms that were funded by local banks to a larger extent reported lower levels of credit rationing. All these firms borrowed from both local and non-local banks, both before and after outbreak of the financial crisis. This reduces any potential sample-selection bias. Since these firms received credit before the crisis by non-local banks – who mostly rely on hard information to make lending decisions – this suggests that their hard-information indicators before the financial crisis were good – or good enough to be funded. It follows that, for the above discussion, also their soft-information quality was good, as well. The unanticipated outbreak of the financial crisis thus allows us to study to what extent this sample of firms, which were good *ex-ante* – both from a hard-information and a soft-information point of view – received funding from local versus non-local banks once their hard-information indicators worsened, conditional on their soft-information quality still remaining good.<sup>7</sup>

In order to do so, we focus on the following tests which allow us to confirm the theory of geographical segmentation – and the respective role of local and non-local banks in using different types of information and lending technologies – we have in mind: First, we study the geographical concentration of local versus non-local banks, and in particular whether a market segmentation exists – in particular, whether local banks are more likely to lend in a smaller set of local credit markets, or to specific industry sectors. If it is the case, this would influence banks' lending strategies as the number of firms and their industry focus would be different. Second, we look at

---

<sup>7</sup> As we already discussed, it is reasonable to assume that borrowers' characteristics that can be identified through relationship lending are unlikely to be correlated with a financial crisis, and less so in a negative way.

the characteristics of firms funded by local versus non-local banks, in order to assess whether local banks vis-à-vis non-local banks specialise in different types of firms. If our conjecture is correct, we should observe firms that rely on local banks to a larger extent to be more opaque on average – e.g. they should be younger, smaller, and potentially more leveraged and riskier than firms that tend to rely on non-local banks to a greater extent. If this is the case, it would also imply that local banks should largely rely on soft information to fund these firms and assess their creditworthiness.

As already mentioned, by only selecting multiple-borrowing firms that have at least one loan from each type of banks (local and non-local), we can control for any firm-specific shock that could affect the lending decisions of local versus non-local banks.

Finally, to rule out a differential impact of the financial crisis on local versus non-local banks which may follow from different exposure towards different types of firms, we study both the extensive and the intensive margin of credit.

Results from all these tests are presented in greater detail in the next sections.

### **3. Measuring bank localism**

In this paragraph we discuss how we define local banks and how we use such categorization in our analysis. Bank localism can be described by a set of characteristics – e.g. narrow geographical outreach, simple organizational structure – that allow local lenders to have a stronger bond with the local economy than non-local banks. The existing literature has in fact identified local banks as financial institutions either with fewer managerial levels (Berg and Udell, 2002), or that are geographically concentrated in few local credit markets (Hannan and Prager, 2004; Hannan 2006), or with relatively short distances between the headquarter and the branches (Alessandrini et al., 2010; Jiménez et al., 2009). In contrast with these papers, we introduce a novel measure of bank

localism that takes simultaneously into account banks' geographical concentration in local credit markets, and the relative size – in terms of volume of credit – of these markets.

The underlying idea is that, to be classified as local, not only banks should be concentrated in fewer local credit markets, but these markets should be relatively small – local banks should be the main lenders in those markets. It is precisely through their relative importance for a certain credit market that local banks can collect soft information to a higher extent than non-local banks. Think of a bank that operates in very few small-size credit markets. This bank will probably lend to firms that are connected among each other because they belong to the same supply chain or industrial cluster. This, in turn, allows this bank to play a key role in those markets, and to gather a detailed understanding of the economic, but also of the social and cultural context it operates in. Such bank corresponds exactly to a local bank.

Our measure of bank localism is built matching different data sources: first, the Italian Credit Register, which contains information on the volumes of credit each bank lends to each firm. Second, the 2001 Italian National Census carried out by the Italian National Statistics Institute (ISTAT), which identifies 686 Local Labour Market Areas (LLMAs) throughout the Italian territory.<sup>8</sup> This is used to relate each firm's municipality to its corresponding LLMAs, and to calculate the amount credit lent by banks in each LLMA.<sup>9</sup>

Our measure of localism consists in a simplified version of Williams' index, which was first used to study firms' specialization across local labour market areas (Williams, 1991).<sup>10</sup> The index is

---

<sup>8</sup> Yet, firms in our dataset are spread across a lower number of LLMAs. Therefore, we end up with 393 LLMAs in our final dataset from the initial 686 LLMAs. LLMAs are defined as a set of adjacent municipalities linked by daily commuter flows for work purposes. More precisely, a LLMA “*is a cluster of municipalities whose self-containment in terms of commuting passes a minimum threshold* [in terms of number of residents and available jobs]” (Casado-Díaz, 2007).

<sup>9</sup> The adoption of LLMAs as a proxy for local credit markets allows us to capture very precisely the extent to which a bank operates in the territory. At the same time, LLMAs, because of their dimension and number, are able to incorporate much more variation than Italian provinces. In Italy, there were 107 provinces versus 686 LLMAs (data refer to 2010).

<sup>10</sup> Williams' index is used to classify firms into more or less specialized, according to both their production shares over one or several sub-markets and to the relative size of these sub-markets compared to the overall production market. Farabullini and Gobbi (2000) later apply this index to the Italian banking sector to define banks' degree of specialization. Their measure takes into account the number of local credit markets where banks operate (through loans, deposits, and bank offices), and the weight of these local credit markets on the national credit market. To the best of our knowledge, however, we are the first to adopt Williams' index to generate a measure of bank localism.

constructed at the bank level, is time variant, and identifies the extent to which a bank  $j$  in year  $t$  that operates in  $k=1,2,\dots,m$  LLMA is local, based on the volumes of credit lent in each of those LLMA. It is computed as follows:

$$local_{jt} = \sum_{k=1}^m \left( \frac{c_{jkt}}{c_{jt}} - \frac{c_{kt}}{c_t} \right)^2 \quad (1)$$

where for all LLMA where bank  $j$  operates in year  $t$ : i)  $c_{jkt}$  is the amount of credit bank  $j$  lends in LLMA  $k$  in year  $t$ ; ii)  $c_{jt}$  is the total amount of credit lent by bank  $j$  in year  $t$ ; iii)  $c_{kt}$  is the amount of credit borrowed in the LLMA  $k$  by all firms headquartered in LLMA  $k$ , and iv)  $c_t$  is the total amount of credit lent in year  $t$ .

According to such measure, a bank will be more local the higher is its credit concentration across fewer LLMA, and the lower is the weight – in terms of credit volume – of these LLMA on the overall credit market. This measure ranges from zero to two: low levels of the index are associated with banks that spread their credit equally across local credit markets in accordance with their relative sizes – these banks are thus classified as non-local. High values of the index, on the contrary, identify local banks – those that tend to concentrate their credit over smaller local credit markets. Consider for instance the case of a credit market characterized by two local credit markets (A and B) and four banks (Bank 1, 2, 3 and 4). Table 1 below shows two different hypothetical scenarios. We are interested, in particular, to assess Bank 4's degree of localism under each of them.

Table 1. Examples of the index computation

Panel A	Market A	Market B	A+B	index
Bank 1	10	100	110	0.00
Bank 2	10	100	110	0.00
Bank 3	10	100	110	0.00
<b>Bank 4</b>	10	0	10	1.56
Total credit	40	300	340	

  

Panel B	Market A	Market B	A+B	index
Bank 1	10	100	110	0.00
Bank 2	10	100	110	0.00
Bank 3	10	100	110	0.00
<b>Bank 4</b>	0	10	10	0.02
Total credit	30	310	340	

In the first scenario (Table 1, Panel A), Bank 4 lends all its credit in Market A, which is small compared to Market B, and populated by banks that lend relatively small, but identical credit volumes. On the contrary, Bank 4 does not lend at all in Market B, which is larger, and where other banks operate on a much larger scale. Market A is very important for Bank 4 – all its credit is concentrated there – and the bank itself is relatively important for the local market (its market share is 25 per cent). Therefore, the index of localism takes a high value, as the bank can be considered local, for our purposes.

Conversely, consider the scenario depicted in Panel B, Table 1. In this case, Bank 4 lends all its credit in a much larger credit market, Market B, where other banks have a larger and deeper presence. On the contrary, it does not lend at all in a smaller credit market like Market A. In this case, while the market is still very important for the bank (all its credit is concentrated there), the importance of Bank 4 in Market B as shown in Panel B is largely undermined by the presence of its competitors, but also by the fact that the share of credit lent by Bank 4 over the total credit lent in Market B is marginal – its market share is less than 3 per cent. Also, Bank 4 is not involved at all in Market A, where it could have been much more important given the relatively low presence of Bank 1, 2, 3. In this case, according to our index, this bank will be classified as less local than in Panel A.

Compared to the existing measures of bank localism, our index includes two novel aspects: First, banks' geographical concentration is defined not only based on the number of credit markets where a bank operates, but also on the volume of credit disbursed in those markets. In this sense, our index considers the level of bank competition in terms of loans at the local credit market level. A bank that operates in more than one local credit market may be local or not depending on the relative size of these markets with respect to the overall Italian credit market.<sup>11</sup> Second, our measure has the advantage of evaluating the importance of each bank in every single market, thus going beyond the mere bank-size dimension, traditionally considered as a key aspect for localism. For instance, a bank that is classified as small according to the dimensional criterion, not necessarily will be local.

### *3.1 Banks' localism versus other banks' dimensions*

Table 2 below shows how banks in our sample are classified based on our index of localism, as well as their size.<sup>12</sup> Interestingly, Table 2 shows that almost 45% of minor and small banks in our sample are classified as not local. A potential explanation for this apparently contradictory result is that these banks operate in markets with high bank competition and therefore, despite they are small, they fail in becoming the main local lender for their firms.<sup>13</sup> At the same time, one big bank out of nine is classified as local. Though it might seem surprising at first glance, this big, although local bank, indeed operates in 5 local credit markets only – vis-à-vis an average 71 for the other 8 big banks.<sup>14</sup>

---

<sup>11</sup> Still, as we will discuss in the next section, the number of LLMA's were local banks operate is significantly lower than for non-local banks.

<sup>12</sup> The dimensional information is provided by the Bank of Italy, Annual Report 2009. Bank classification based on size builds on banks' assets. In addition, as our index is expressed as a continuous variable, to ease banks' classification we now consider the median of its distribution and classify intermediaries whose index is above the median as local, and non-local otherwise. Table 2 shows 346 observations instead of 348 as the dimensional classification is not available for two banks in our sample.

<sup>13</sup> We also conduct a similar analysis based on banks' institutional category. The analysis reveals that almost 80% of Italian cooperative banks are classified as local; on the contrary, only one-fourth of mutual banks fall under this definition. Similarly, about one-fifth of joint-stock companies (Italian "*Società per azioni*") are local, as well.

<sup>14</sup> More interestingly, all the credit lent by this big, but local, bank, is concentrated in two sectors only: energy and services. Big, non-local banks, instead, all lend more than 70% of their credit in the manufacturing sector.

Table 2. Banks' classification (local *versus* other characteristics)

Bank classification based on size and localism					
	Major banks	Big banks	Medium-sized banks	Minor and small banks	Total
<b>Non-local banks</b>	6	8	27	132	173
<b>Local banks</b>	0	1	0	173	174
<b>Total</b>	6	9	27	305	346

Finally, we compute a few balancing tests to study average differences between local and non-local banks in terms of geographical concentration (expressed in terms of numbers of local credit market areas they lend to), total credit disbursed, and type of industry sector they focus their lending activities on. Results are shown in Table 3 below. Local banks operate on average in 2 LLMA's, vis-à-vis 30 LLMA's for non-local banks. Moreover, the total outstanding loan portfolio of local banks in 2007 was 3% the total outstanding loan portfolio of non-local banks, suggesting that local banks give way fewer, and smaller loans than non-local banks. Finally, we look at whether local banks specialise in different industry sectors compared with non-local banks.<sup>15</sup> We find that local banks are significantly more likely to lend to firms operating in Services, whereas non-local banks are significantly more likely to lend to firms in the Manufacturing sector.

Table 3. Local versus non-local banks: number of LLMA's, credit disbursed, and sector of firms

	Local banks (1)	Non-local banks (2)	Difference (2) – (1)
Number of LLMA's	1.912 (0.124)	30.505 (3.917)	28.591*** (3.885)
Total credit disbursed (log)	13.903 (0.157)	17.232 (0.150)	3.329*** (0.217)
Share of firms in Services	0.635 (0.024)	0.695 (0.012)	0.060** (0.027)
Share of firms in Manufacturing	0.330 (0.022)	0.272 (0.012)	-0.058** (0.025)
Number of Observations	172	176	348

<sup>15</sup> It must be noticed here that almost 97% of the firms in our sample operate either in Manufacturing (71%) or Services (26%).



## 4. Data and Descriptive Statistics

### 4.1. Data

Our novel dataset is built from different sources. The first set of data is obtained from the Bank of Italy’s survey of industrial and service firms with at least twenty workers (INVIND). This survey is carried out once a year on a stratified sample of Italian firms and contains unique questions designed to elicit information on their financing needs and the existence of credit rationing. We match the firms in the INVIND sample with the Italian Central Credit Register (*Centrale dei Rischi*). This dataset contains information on the credit borrowed by Italian non-financial firms to banks operating in Italy. Merging these two data sources allows us to assess every single loan amount borrowed by each firm in the INVIND survey from any bank operating in the Italian credit market. We then obtain firms’ balance sheets information from the CERVED dataset, comprising official records filed with Italian Chambers of Commerce and reported by the Cerved Group. Finally, banks’ characteristics are obtained from both Supervisory Reports and Bank of Italy Annual Reports. For each bank in the dataset, we classify them into local and non-local, based on the index we discussed in Section 3.<sup>16</sup> By matching these data sources, we end up with a panel 2,373 firms borrowing from 348 banks – both local and non-local – over the years 2007 and 2008.

### 4.2. Descriptive Statistics

Our dataset allows us to create a measure of credit rationing at the firm level. This is constructed using the unique information we obtain from the INVIND survey. We classify as

---

<sup>16</sup> Banks are classified as local or not local depending on whether their index of localism is above or below the median of the index distribution.

credit rationed firms that were in need of additional funds but stated that their funding request was turned down by the financial intermediaries they contacted.<sup>17</sup>

Table 6 in the Appendix summarises the characteristics of the firms and the banks in our sample, evaluated in 2007. Panel A shows that three per cent of firms reported experiencing credit rationing. This share is consistent with findings from other studies – ECB’s SAFE survey in the EU countries,<sup>18</sup> or surveys conducted in France by Insee and OSEO.<sup>19</sup> In terms of balance sheet characteristics, firms are on average 42 years old and 63% of them has more than 50 employees. Consistent with these data, firms’ average ROA is 1.469. Firms appear moderately risky: the average risk rating in our sample is 4.6 on a scale from 1 (very safe) to 9 (very risky). Panel B of Table 5 shows descriptive statistics for banks’ variables. Banks’ size is expressed as a discrete index going from 1 (major banks) to 7 (minor banks). The median bank’s size in our sample is 5, revealing that half of the banks in our sample are small and minor banks. The average value of the index of localism, computed in Section 3, is 0.571.

In terms of relationship lending variables, Panel C of Table 6 shows that the median number of bank relationships for each firm is 7, suggesting that most of the firms in our sample engage in multiple bank lending relationships.<sup>20</sup> In addition, only 7% of the bank-firm relationships in place in 2007 were interrupted in 2008 suggesting that once formed, such relationships are pretty stable.

---

<sup>17</sup> Our measure of credit rationing is obtained by combining the outcomes of two separate questions of the INVIND survey: in the first question, firms were asked whether they needed more funding than what they had actually received; in the second, firms were asked whether the banks they addressed to receive more funding had eventually turned down their credit request. Answers to both questions are reported in binary form. Both questions are from Part 5 (Firm Funding) of the survey. The firms were asked to answer first to question V316 “*You should indicate if, given the firm’s cost and collateral conditions, you ask for more debt load*”; then to question V267 “*Please indicate if the contacted financial intermediaries proved not to be willing to increase your funding volume*”. We classify firms reporting a positive answer to both questions as financially constrained.

<sup>18</sup> Survey on the access to finance of SMEs in the euro area, available at <http://www.ecb.int/stats/money/surveys/sme/html/index.en.html>. We thank Denis Fougère and Patrick Sevestre for pointing this out.

<sup>19</sup> [http://www.oseo.fr/notre\\_mission/publications/etudes\\_et\\_rapports/generalistes](http://www.oseo.fr/notre_mission/publications/etudes_et_rapports/generalistes).

<sup>20</sup> We will discuss the extent to which firms in our sample borrow from more than one bank in greater detail below.

## 5. Identification Strategy

Our identification strategy exploits the heterogeneity in banks' reliance on soft information to study the lending strategies of local versus non-local banks before and after the outburst of the 2007-08 Financial Crisis. It builds on the assumption that the extent to which banks use soft information positively correlates with their level of localism.<sup>21</sup>

We test this prediction by looking at a set of correlations between firms' characteristics and their probability to be funded by local banks – a variable that we call  $\overline{local}_{i,2007}$ . We employ a sample of 2,500 firms that either borrow from both local and non-local banks or firms that borrow from only one type of banks.

Our firm-level variables include among others size, age, profitability, riskiness assessment – taken from both the INVIND and the CERVED dataset and evaluated the year before the financial crisis started.  $\overline{local}_{i,2007}$  is the measure of bank localism constructed in (1), averaged at the firm level. This expresses the extent to which firms are funded by local versus non-local banks and it is computed as follows:

$$\overline{local}_{it} = \sum_{j=1}^n \left( \frac{c_{ijt}}{c_{it}} * local_{jt} \right) \quad (2)$$

that is, for all the banks that lend to firm  $i$  in year  $t$ , we take the weighted average of the banks' index of localism ( $local_{jt}$ ), the weights being the share of credit borrowed by firm  $i$  from bank  $j$  in year  $t$  over the total amount of credit borrowed by firm  $i$  in year  $t$ .<sup>22</sup>

In order to control for potential endogeneity, we look at this set of correlations before the outburst of the financial crisis. Results are shown in Table 4 below.

---

<sup>21</sup> This is because of the geographical concentration of local banks in fewer, and smaller, local credit markets compared to non-local banks.

<sup>22</sup> We construct the weights using loan data from the Italian Credit Register.

Table 4. Correlation matrix – firms' variables

This table reports correlation coefficients between firm variables. We include firms' ROA, ROE, EBITDA, size (a dummy which takes the value of one if the firm has more than 50 employees), age, leverage and rating. The first column shows correlations between *Local bank* and firms' balance sheet variables. *Local bank* is computed as the weighted average at the firm level of banks' index of localism, the weights being the shares of credit borrowed by the firm from each funding bank. \*\*\* correlation coefficient significant at 1 per cent; \*\* at 5 per cent; \* at 10 per cent.

	local bank	ROA	ROE	EBITDA	size	age	leverage	rating
local bank	1							
ROA	-0.0089	1						
ROE	0.0095	0.1232***	1					
EBITDA	0.0148***	0.6644***	0.1039***	1				
size	-0.1382***	0.0819***	0.0327***	0.0857***	1			
age	-0.0549***	0.039***	-0.0043	0.0113	0.1102***	1		
leverage	0.1173***	-0.4494***	-0.032***	0.3378***	-0.0704***	-0.1134***	1	
rating	0.0831***	-0.5508***	-0.0622***	-0.476***	-0.0395***	-0.146***	0.7444***	1

Consistent with our assumption, there is a positive relationship between firms' reliance on local banks and their opaqueness: age and size are negatively correlated with local-banks reliance, while leverage is negatively correlated. Interestingly, both the EBITDA and the overall risk assessment are positively correlated with *local bank*.

Since we observe a potential selection issue for firms funded by local versus non-local banks, this further motivates the need to conduct our analysis only with firms that in 2007 borrowed from both local and non-local banks. This restricts our sample to 2,373 firms, thus dropping 5% of the firms from the initial sample as these were borrowing exclusively from either local or non-local banks. Although the share of firms we are discarding from the analysis is very small, we conduct a set of balancing checks to study how different is the sample of firms that engaged in single borrowing in 2007 vis-à-vis multiple borrowing. Results are shown in Appendix, Table 7. Multiple-borrowing firms appear significantly larger on average (in terms of assets), they borrow more credit, and they are significantly more likely to operate in the Services sector. No differences

between the two samples can be detected in terms of profitability, age, number of employees, or the reliance on local-banks funding. All in all, results from Table 7 suggest that by discarding single-borrowing banks, we are still considering firms that are quite similar and which, on the other hand, borrow the largest share of credit in the market.

### 5.1 Credit rationing during the 2007-08 Financial Crisis

Before turning to the main analysis, we study whether firms' characteristics worsened during the financial crisis. This exercise is used to understand whether firms' characteristics worsened in 2008, compared with 2007. We estimate the following regression equation at the firm level:

$$firm\ characteristic_{i,t} = \beta_0 + \beta_1 crisis_t + \varphi_i + \varepsilon_{i,t} \quad (3)$$

where  $firm\ characteristic_{i,t}$  is a set of firms' characteristics measured in year  $t$ , with  $t=2007;2008$  and  $crisis_t$  is a dummy that takes the value of zero in year 2007 and one in year 2008.  $\varphi_i$  are firms fixed effects. Results from equation (3) are shown in Table 5 below.

Table 5. Before and after the crisis - Firms' variables

This table reports results from estimates used to test differences across firms' balance sheet characteristics before and after the financial crisis. We include as dependent variables the probability a firm reports being credit rationed, firms' ROA, ROE, EBITDA, size (a dummy which takes the value of one if the firm has more than 50 employees), age, leverage and rating.  $crisis$  is a dummy that takes the value of one in 2008 and zero in 2007. OLS estimates are shown. Robust standard errors in brackets. \*\*\* coefficient significant at 1 per cent; \*\* at 5 per cent; \* at 10 per cent.

Dep. Variable	p(credrat)	ROA	ROE	EBITDA	size	age	leverage	rating
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
crisis	0.054*** (0.007)	-1.054*** (0.181)	-15.186* (8.836)	-1.653*** (0.191)	0.004 (0.004)	-0.021 (0.136)	-5.338*** (1.359)	0.095 (0.084)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. of firms	2,373	2,373	2,373	2,373	2,373	2,373	2,373	2,373
Observations	4,257	4,257	4,257	4,257	4,257	4,257	4,257	4,257

Results from Table 5 show that firms' hard-information outlook became poorer in 2008 compared with 2007. The probability that firms report credit rationing almost doubled during the crisis, with 5.5% per cent of firms reporting credit rationing in 2008 versus less than 3% in 2007, as shown in Table 1. Moreover, during the crisis, firms' balance sheet indicators significantly worsened. Firms became on average less profitable and reported lower revenues. The average leverage however significantly decreased, potentially reflecting the increase in credit rationing.<sup>23</sup>

Keeping results from Table 5 in mind, we study whether firms reported a lower credit rationing from local banks than from non-local banks, in 2008 vis-à-vis 2007. Our hypothesis is that firms who received funding during periods of financial stability from both local and non-local banks – which is suggestive of good hard-information and soft-information indicators – should have experienced larger credit tightening during periods of financial downturns by non-local lenders. This is because during such times their hard-information outlook worsened and non-local banks were less able than local banks to collect soft information to assess whether their existing customers were still worth funding. We use a Difference-in-Difference approach to compare the probability that firms with higher versus lower reliance on local banks report to be credit rationed across two periods, the year before and after the financial crisis. We estimate the following regression equation at the firm level<sup>24</sup>, only with those firms that in 2007 borrowed from both local and non-local banks, to account for credit demand effects:

$$p(\text{credrat})_{it} = \beta_0 + \beta_1 \overline{\text{local}_{i,2007}} + \beta_2 \text{crisis}_t + \beta_3 (\overline{\text{local}_{i,2007}} * \text{crisis}_t) + \varepsilon_{it} \quad (4)$$

where  $p(\text{credrat})_{it}$  is the probability that firm  $i$  reports having experienced credit rationing (derived from INVIND);  $\text{crisis}_t$  is a dummy which takes the value of one in 2008 and zero otherwise, and  $\overline{\text{local}_{i,2007}}$  is our measure of bank localism computed at the firm level, as shown in

---

<sup>23</sup> The leverage is indeed defined as debt over equity.

<sup>24</sup> This is because the self-reported measure of credit rationing obtained from INVIND is a firm-level variable.

(2).<sup>25</sup> We are particularly interested in the sign and the significance of  $\beta_3$ , the Diff-in-Diff coefficient. We use both a probit and a linear probability model to estimate equation (4). Results are shown in Table 8. Column (1) shows the marginal effects of our estimates (using the probit model) without adding controls. The coefficient of the interaction term  $\overline{local}_{i,2007} * crisis_t$  is negative and significant, revealing that the higher is the firm's reliance on local banks, the lower the likelihood to report having being credit rationed during the financial crisis. We then add firms' and banks' controls in further specifications shown in column (2), (3), (4). Controls include firms' age, assets, number of employees, ROA, ROE and rating, as well as a set of dummies indicating the industry the firm belongs to and the local credit market in which the firm is located. We also add the firm's number of bank lending relationships and whether the firm's main lender – the bank which granted the firm the highest share of credit – belongs to one of the top five banking group in Italy. Finally, we include a set of banks' characteristics averaged at the firm level using an approach akin to how we computed  $\overline{local}_{i,2007}$ . This set of variables comprises banks' size, the share of loans not funded on the retail market and banks' capital ratio. We estimate the specification with controls using both a probit and a Linear Probability Model, in column (2) and (3), respectively.  $\beta_3$  remains negative and significant,<sup>26</sup> even after including banks' size, confirming that our measure of localism captures a different dimension from banks' dimension. Finally, Column (4) of Table 8 shows estimates from Equation (4) using a Linear Probability Model with location-age-sector-size Fixed Effects. Given that the dependent variable,  $p(credrat)_{it}$ , has limited variability, the inclusion of firm Fixed Effects in the Diff-in-Diff estimation might lead to biased estimates (Angrist and Pischke, 2008).<sup>27</sup> To still account for firms' unobserved heterogeneity, we use a set of granular fixed effects in a similar spirit as Degryse et al. (2018).

---

<sup>26</sup> It must be noted that due to variable collinearity there is a significant drop in the number of observations in the estimates shown in Column (2). However, estimates using a Linear Probability Model (column 3 of Table 2) confirm the main results.

<sup>27</sup> This is because we would be estimating (5) on a balanced panel of firms – thus excluding those firms that enter or exit because of funding constraints.

Results are shown in Column (4) of Table 8.  $\beta_3$  is still negative and significant, and with similar magnitude as in the previous specifications.

All in all, Table 8 shows that, conditional on being funded by both local and non-local banks, firms reported a lower rate of credit rationing during the financial crisis, the higher their reliance on local banks. These results are robust to the inclusion of both firms' and banks' variables. This confirms our hypothesis that when hard-information variables significantly worsened – as shown in Table 5 – lenders who rely on soft-information to a larger extent were less likely to curtail credit to firms.

## 5.2 Extensive margin of credit

The main result from Table 8 is that firms experienced a lower credit tightening during the financial crisis from lenders that rely on soft-information to a higher extent. The underlying intuition is that local banks keep funding their customers when hard-information worsens, precisely because they rely on soft-information to compensate for “bad” hard-information indicators.

To test this hypothesis, we use data from the Italian Credit Registry, which provides information on every loan borrowed by each firm in our sample. For each firm-bank relationship, we know in which year the loan was disbursed, its amount, and whether the lender for that particular loan was a local or non-local one, based on the definition we previously discussed.

This allows us to compute the extensive margin of credit and to study whether local lenders were indeed less likely than non-local ones to cut credit to their existing customers.

We estimate the following regression equation using a probit model:

$$p(\text{terminate})_{ij2008} = \gamma_0 + \gamma_1 dlocal_{j2007} + \varepsilon_{ij} \quad (5)$$

where the dependent variable,  $p(\text{terminate})_{ij2008}$  is the probability that a lending relationship between firm  $i$  and bank  $j$  that existed in 2007 is terminated in 2008, and  $dlocal_{j2007}$  is a dummy



that takes the value of one if bank  $j$  is local and zero otherwise.<sup>28</sup> Results from equation (5) are shown in table 9, column (1).  $\gamma_1$  is negative and statistically significant: local banks were less likely than non-local banks to cut relationships with their current customers during their financial crisis. The coefficient of  $dlocal_{j2007}$  is negative and significant also after controlling for firms' and banks' characteristics, in column (2) and (3) respectively. Taken together, results from table 8 and 9 indicate that local banks kept funding their customers even if their hard-information indicators looked poorer – possibly because they made use of soft-information to identify good borrowers. Results from Table 9 confirm the prediction we formulated in Section 2: when the quality of a firm worsened, as it was the case in 2008, banks relying on soft information kept lending to their existing customers to a larger extent.

## 6. Robustness Checks

Our analysis so far has shown that firms borrowing from local banks in 2008 reported a lower rate of credit rationing than firms borrowing from not local banks. This result can be explained by the fact that local banks make a greater use of soft information compared with non-local banks. During periods of financial downturns, when hard-information deteriorates, local banks can use soft-information to validate their lending choices and keep their old customers.

Yet, there are potentially other explanations for our results: first, the lower credit rationing reported by firms predominantly funded by local banks could be driven by a heterogeneous impact the financial crisis had on the credit supply of local versus non-local banks. According to this view, local banks – who are indeed significantly more likely to be small than non-local banks – were subject to less strict capital regulatory requirements than not local banks during the financial crisis. It follows that local banks might have suffered from the liquidity contraction following the collapse of Lehman Brothers to a lower extent than non-local banks. This, in turn,

---

<sup>28</sup> We take the median of  $local_{j2007}$  to identify whether a bank is local or not.

might have translated into a higher funds availability for local banks, thus explaining why these lenders were less likely to tighten credit to their borrowers.

Second, local banks might have been less likely to turn down existing relationships during the financial crisis not because they were able to identify and keep funding good borrowers thanks to the use of soft information, but as a result of a “zombie-lending” strategy. Local banks might have lent to customers at risk of financial distress to “keep them alive”. The reason for such behaviour is quite understandable: having limited diversification strategies – and also relative larger exposure towards the firms they fund – the losses local banks would incur in case of their customers’ bankruptcy would be important, and might undermine the financial stability of the bank itself.

In what follows, we show that none of these competitive hypotheses find support in the data.

### 6.1. Intensive margin of credit

We first look at the intensive margin of credit to study whether there are any differences in the credit supply of local versus non-local banks that could justify our results. We estimate the following equation at the bank level:

$$\Delta \log(\text{credit})_{jt} = \gamma_0 + \gamma_1 dlocal_{j2007} + \gamma_2 crisis_t + \gamma_3 (dlocal_{j2007} * crisis_t) + \epsilon_{jt} \quad (6)$$

where the dependent variable is the growth rate of credit of bank  $j$  in year  $t$ . This is constructed using data from the Credit Register.<sup>29</sup>  $dlocal_{j2007}$  is a dummy that equals to one if bank  $j$ ’s index of localism  $local_{jt}$  is above the median value of the index in year 2007, and zero otherwise. We introduce the interaction term  $dlocal_{j2007} * crisis_t$  and study whether, during the crisis, local banks lent to a greater extent than non-local banks.

Results from equation (6) are reported in Table 10 using OLS. We also include bank fixed effects in Column (2). As expected, the coefficient of the  $crisis_t$  dummy reveals a dramatic slow-down in

---

<sup>29</sup> We use also Credit Registry data from 2006 to compute credit growth rate in 2007.

the credit growth at the bank level both in column (1) and (2). In addition, the coefficient of  $dlocal_{j2007}$  is negative and significant in all specifications. Its sign and significance reveal that on average, the growth rate of credit from local banks is significantly lower than for non-local banks. However, the Diff-in-Diff coefficient,  $\gamma_3$ , is never significant. This suggests that during the financial crisis local banks did not lend more than non-local banks. Results from Table 10 rule out the hypothesis that our results are driven by differences in the credit supply between local and non-local banks resulting from different regulatory constraints. On the contrary, they corroborate our intuition that differences in lending are driven by a different type of relationships local versus non-local banks have with their customers.

## 6.2. Zombie-lending strategies

To rule out that our results are driven by a zombie-lending strategy, we study the extensive margin of credit and look at the characteristics of the firms that local banks were more likely to keep funding during the financial crisis. We estimate the following regression equation at the loan level:

$$p(terminate)_{ij2008} = \gamma_0 + \gamma_1 dlocal_{j2007} + \gamma_2 firm\ characteristic_{i,2007} + \gamma_3 dlocal_{j2007} * firm\ characteristic_{i,2007} + \varepsilon_{ij} \quad (7)$$

where  $p(terminate)_{ij2008}$  is the probability that a firm-bank relationship that was in place in year 2007 was terminated in 2008.  $firm\ characteristic_{i,2007}$  is a set of firms' characteristics including ROA, revenues, size, leverage, and rating, evaluated before the financial crisis. We include the interaction term between  $firm\ characteristic_{i,2007}$  and  $dlocal_{j2007}$  to precisely assess which firms local banks were less likely to terminate existing relationships. Results from equation (7) are shown in Table 11. If our results were to be explained by a zombie-lending story, we should observe local banks to be less likely to terminate existing relationships with firms with worse balance sheet characteristics – that is, less profitable, smaller, riskier firms. This is however

not the case –  $\gamma_3$  is not significant when we look at the interaction term between  $dlocal_{j2007}$  and firms’ ROA or EBITDA, for instance. However, local banks appear less likely to cut existing relationships with high-leverage firms. Having high leverage does not imply that the firm is “bad”, rather that it is using more resources possibly to invest in high-risk/high-return business activities. Still, being high leveraged may affect a firm’s rating: this might explain why in column (5) we find local banks to be less likely to terminate existing relationships with firms with worse rating.

All in all, our results are consistent with a “soft-information” story – local banks kept funding opaque firms, which however do not appear to be less profitable or smaller firms. This corroborates our original Prediction formulated in Section 2: as the firms’ hard-information quality worsened, only local banks kept lending, provided that soft information revealed that the firm’s quality is good.

Finally, we also look at whether local banks were less likely to terminate existing relationships with firms with whom they had a relatively high credit exposure. It might be in fact the case that they kept funding these firms precisely because they wanted to be sure they could retrieve their outstanding credit. Column (7) of Table 11 however shows that the interaction term between  $dlocal_{j2007}$  and  $share\ credit\ bank_{i,2007}$  is positive and significant. This suggests that local banks, during the financial crisis, were less likely to interrupt relationships with firms they were less exposed to. Results from Table 11 lead us reject a zombie-lending story explaining our results, and once more confirm our hypothesis that local banks lent to a higher extent during the financial crisis precisely because they used soft information to a higher extent.

## 7. Conclusions

In this paper, we show that soft information can lead local lenders to grant credit, in cases when hard information would suggest the opposite.

We use data from the Italian credit market and we compare the behaviour of local versus non-local banks using a novel dataset that contains information on loans, as well as on firms' and banks' characteristics, before and after the 2007-08 Financial Crisis. Our identification strategy exploits the heterogeneity in banks' reliance on soft information to study the lending strategies of local versus non-local banks in 2007 vis-à-vis 2008. It builds on the assumption that local banks use soft information to a higher extent than non-local banks but they rely on hard information to a similar extent.

Our results show that firms predominantly funded by local banks reported a lower credit rationing in 2008 compared with 2007. We also find that local banks were less likely to terminate existing relationships with their customers during the financial crisis, suggesting that local banks continued funding their clients even when borrowers' balance sheet variables worsened. Our results cannot be explained by demand effects, neither by a “zombie-lending” behaviour or by different impacts the financial crisis had on the credit supply of local versus local firms. This leads us to conclude that thanks to their greater reliance on soft information, local lenders supported their customers to a higher extent during bad times. Taken together, our findings suggest that thanks to relationship lending firms borrowing from local banks to a higher extent experienced more credit stability during the financial crisis, compared to firms borrowing from not local banks. Yet, one important *caveat* to our findings is that they reflect changes in a limited time span – we indeed study loan outcomes and firms' financial constraints only in the year before and after the collapse of Lehman Brothers. Therefore our results do not account for the longer-term, real effects of the financial crisis – for instance, for the differential impact of the financial shock on tradeable versus non-tradeable sectors – which may have affected the lending decisions of local versus non-local banks and firms' probability to report being credit rationed in later years.

All in all, our paper highlights the importance of relationship lending, particularly in a period of financial distress. Local banks, which rely more on soft information than not local banks, played a more supportive role towards the firms they had already a lending history with, thus proving to

be important buffers against negative financial shocks for their customers, at least in the period immediately following the Financial Crisis.

## **Acknowledgements**

The views expressed herein are solely of the authors and do not reflect those of Bank of Italy. The authors wish to thank, without implicating, Antonio Accetturo, Luigi Cannari, Piero Casadio, Riccardo De Bonis, Silvia Del Prete, Alessio D'Ignazio, Emilia Garcia-Appendini, Claire Lelarge, Kebin Ma, Massimo Omiccioli, Steven Ongena, Marcello Pagnini, Paola Rossi, David Scharfstein, Enrico Sette, Patrick Sevestre and seminar participants at the Università Politecnica delle Marche, at the XX International Tor Vergata Conference on Money, Banking and Finance, at Banque de France, Bank of Italy and University of Zurich for their useful comments and advices. All errors are our own.

## **References**

- Agarwal, S., Hauswald, R., 2010. Distance and private information in lending. *Review of Financial Studies* 23, 2757–2788.
- Albertazzi, U. and D.J. Marchetti (2010). “Credit supply, flight to quality and evergreening: an analysis of bank-firm relationships after Lehman.”
- Alessandrini P., Presbitero, A.F., Zazzaro, A., 2009. Banks, Distances and Financing Constraints for Firms. *Review of Finance* 13, 261-307.
- Berger, A.N., Udell, G.F., 2002. Small Business Credit Availability and Relationship Lending: The Importance of Bank Organisational Structure. *Economic Journal* 112, 32-53.
- Berger, A.N., Miller, H., Mitchell, M.A., Rajan, R.G., Stein, J.C., 2005. Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics* 76, 237-269.

- Bonaccorsi di Patti E., Sette, E., 2012. Bank balance sheets and the transmission of financial shocks to borrowers: evidence from the 2007-2008 crisis. *Temi di discussione (Working Papers)* 848, Banca d'Italia.
- Casado-Díaz, J. M., 2000. Local labour market areas in Spain: a case study. *Regional Studies* 34, 843-856.
- Degryse, H., De Jonghe, O., Jakovljević, S., Mulier, K., & Schepens, G. (2017). *Identifying Credit Supply Shocks with Bank-Firm Data: Methods and Applications*.
- DeYoung, R., Hunter, W.C., Udell, G.F., 2004. Whither the Community Bank?. *Journal of Financial Services Research* 25, 81-84.
- DeYoung, R., Frame, W.S., Glennon, D., Nigro P., 2011. The Information Revolution and Small Business Lending: The Missing Evidence. *Journal of Financial Services Research* 39, 19-33.
- Farabullini, F. and Gobbi, G., 2000. Le banche nei sistemi locali di produzione, in: Signorini, L.F. (Eds.), *Lo sviluppo locale*, Donzelli, Rome.
- Gambacorta, L., and Mistrulli, P.E., 2011. Bank heterogeneity and interest rate setting: What lessons have we learned since Lehman Brothers?. *BIS Working Papers* 359.
- Garcia-Appendini, E. (2011) "Lending to small businesses: The value of soft information." *mimeo*
- Gobbi, G., Sette, E., 2013. Do Firms Benefit from Concentrating their Borrowing? Evidence from the Great Recession. *Review of Finance* 18, 527-560.
- Hannan, T.H., 2006. Retail deposit fees and multimarket banking. *Journal of Banking & Finance* 30, 2561-2578.
- Hannan, T.H., and Prager, R.A., 2004. The competitive implications of multimarket bank branching. *Journal of Banking & Finance* 28, 1889-1914.
- Jiménez, G., Salas, V., and Saurina, J., 2009. Organizational distance and use of collateral for business loans. *Journal of Banking & Finance* 33, 234-243.
- Kremp, E., Sevestre, P., 2013. Did the crisis induce credit rationing for French SMEs?. *Journal of Banking & Finance*, 37, 3757-3772.

Liberti, J. M. (2003). "Initiative, Incentives and Soft Information: How does delegation impact the role of bank relationship managers?" *mimeo*.

Liberti, J. M. (2005). "How does organizational form matter? Distance, communication and soft information." *mimeo*.

Liberti, J. M., and A. Mian (2009). "Estimating the effect of hierarchies on information use." *The Review of Financial Studies*, 22(10), 4057-4090.

Petersen, M., Rajan, R.G., 2002. Does distance still matter? The information revolution in small business lending. *The Journal of Finance* 57, 2533-2570.

Presbitero, A.F., Udell, G.F., Zazzaro, A., 2014. The Home Bias and the Credit Crunch: A Regional Perspective. *Journal of Money, Credit and Banking* 46, 53-85

Stein, J.C., 2005. Information production and capital allocation: Decentralized vs. hierarchical firms. *The Journal of Finance* 57, 1891-1921.

Stiglitz, J.E. and Weiss, A., 1981. Credit rationing in markets with imperfect information. *The American Economic Review*, 71(3), pp.393-410.

Williams, R.A., 1991. Measuring submarket specialisation by firms. *Economic Letters* 36, 291-416.



## Appendix

Table 6. Descriptive Statistics at baseline

	Variables	Definition	Source	median	mean	sd
Panel A						
<b>Firm variables</b>	p(credrat)	=1 if the firm reports being rationed	INVIND	0	0.027	0.163
	ROA	Firm's profit over total assets	CERVED	0.868	1.526	6.115
	rating	Risk assessment on a scale from 1 to 9, where 1: very low risk and 9 very high risk	CERVED	5	4.596	1.776
	leverage	Firm's debt to equity ratio	CERVED	56.0198	52.262	30.441
	age	Years since foundation	CERVED	37	41.772	20.468
	employees	=1 if the firm has 50+ employees	INVIND	1	0.635	0.482
	assets	Log of total assets	CERVED	9.943	9.750	1.390
	EBITDA	Earnings before interest, tax, depreciation and amortization	CERVED	8.242	9.750	9.376
Panel B						
<b>Bank variables</b>	local	Banks' index of localism	Credit Register	0.530	0.571	0.363
	size bank	Banks' size expressed as an index that goes from 1 (large banks) to 7 (very small banks)	Bank of Italy Annual Report	5	5.023	1.438
	capital ratio	Share of loans to supervisory capital	Supervisory Report	0.061	0.101	0.114
	funding ratio	Share of loans to non-financial companies not financed on the retail market (expressed as 1 minus the share of loans to non-financial companies financed on the retail market)	Supervisory Report	-0.120	-0.040	0.427
Panel C						
<b>Bank lending relationships variables</b>	Main bank top 5	The main financing bank belongs to one of the main five banking groups in Italy	Credit Register	0.103	0.053	0.156
	nbank	Firm's number of bank relationships	Credit Register	7	7.979	5.554
	$\Delta \log(\text{credit})$	Growth of credit at bank level	Credit Register	0.272	0.288	0.909
	share bank	Share of credit bank $j$ lends to firm $i$	Credit Register	0.0004	0.0177	0.0852
	p(terminate)	Probability to terminate an existing bank lending relationship in the following year	Credit Register	0	0.068	0.251

Table 7. Balancing checks – single versus multiple-borrowing firms

This table shows balancing checks between the firms considered in the analysis (column (2), multiple borrowing firms that borrow at least from one local and one non-local banks) and single-borrowing firms. Mean t-test are used to assess differences between the two samples. Standard errors in brackets. \*\*\* coefficient significant at 1 per cent; \*\* at 5 per cent; \* at 10 per cent.

	Single-borrowing firms	Multiple-borrowing firms (sample used)	Difference
	(1)	(2)	(2) – (1)
Age	40.583 (1.959)	41.772 (0.420)	-1.189 (1.871)
Share of firms with more than 50 employees	0.606 (0.043)	0.635 (0.010)	-0.029 (0.044)
EBITDA	9.777 (1.396)	8.763 (0.187)	1.013 (0.872)
Total borrowed amount (log)	14.018 (0.554)	6.156 (0.084)	-7.862*** (0.383)
Assets (log)	9.427 (0.154)	9.933 (0.029)	-0.505*** (0.128)
Reliance on local banks ( <i>Local firm</i> )	0.084 (0.017)	0.099 (0.002)	-0.015 (0.012)
=1 if firm in Services	0.047 (0.472)	0.263 (0.009)	0.209*** (0.040)
Number of observations	127	2,373	2,500

Table 8. Credit rationing, local versus non-local banks

This table reports estimates of the determinants of firms' credit rationing. Among regressors, we include our main variable of interest, *local bank*, computed as a weighted average at the firm level of banks' index of localism, the weights being the shares of credit borrowed by the firm from each funding bank; the crisis dummy, and their interaction term, *local bank\*crisis*. The dependent variable  $p(credrat)$  is obtained by combining the outcomes of two separate questions from the Bank of Italy INVIND survey: the first asked whether further funding was needed; the second whether banks had turned down requests for credit. We classify firms reporting a positive answer to both questions as financially constrained. Column (1) and (2) show Probit estimates. Column (3) and (4) show estimates from a LPM, with and without fixed effects. Firms and Banks controls added in the specification shown in column (2) and (3) include: ROA, age, number of employees, log of assets, risk assessment, number of bank links, industry sector (3-digits code), and a dummy for the local credit market the firms is located in. Banks control include: size; funding ratio; capital ratio. Size-Age-Location-Sector FEs are included in column (4). Standard errors clustered at the firm level in brackets. \*\*\* coefficient significant at 1 per cent; \*\* at 5 per cent; \* at 10 per cent. Marginal effects displayed in column (1) and (2).

Dep. Variable	(1) p(credrat)	(2) p(credrat)	(3) p(credrat)	(4) p(credrat)
local bank	0.050 (0.032)	0.115*** (0.043)	0.094* (0.055)	0.085 (0.054)
crisis	0.061*** (0.008)	0.080*** (0.011)	0.063*** (0.009)	0.064*** (0.009)
local bank*crisis	-0.056* (0.033)	-0.094** (0.037)	-0.071* (0.042)	-0.077* (0.043)
Firm Controls	No	Yes	Yes	Yes
Bank Controls	No	Yes	Yes	Yes
Size-Age-Location-Sector FEs	No	No	No	Yes
Observations	4,257	2,148	4,257	4,257
Number of firms	2,373	1,179	2,373	2,373

Table 9. Extensive margin of credit

This table reports estimates of the determinants that a lending relationship between firm  $i$  and bank  $j$  that was in place in 2007 was terminated in 2008. Among regressors, we include our main variable of interest, *dlocal*, which is a dummy that takes the value of one if the bank's index of localism is above the median and zero otherwise. *Share bank* is the relative share of credit lent by bank  $j$  to firm  $i$ . Firms controls added in the specification shown in column (2) include: ROA, age, size (number of employees), leverage, risk assessment, and number of bank links. Banks controls in column (3) include: size; funding ratio; capital ratio. Robust standard errors in brackets. \*\*\* coefficient significant at 1 per cent; \*\* at 5 per cent; \* at 10 per cent. Marginal effects displayed.

Dep. Variable	p(terminate) (1)	p(terminate) (2)	p(terminate) (3)
dlocal	-0.066*** (0.011)	-0.064*** (0.011)	-0.064*** (0.011)
share bank	-0.212*** (0.081)	-0.258*** (0.092)	-0.249*** (0.091)
Firm Controls	No	Yes	Yes
Bank Controls	No	No	Yes
Observations	15,423	14,944	14,944
Number of firms	2,373	2,373	2,373

Table 10. Intensive margin of credit

This table reports OLS estimates of the determinants of banks' annual rate of credit growth and total (log of) credit, at the bank level. We include as regressors our main variable of interests, the dummy *dlocal*, which takes the value of one if the bank's index of localism is above the median and zero otherwise; the *crisis* dummy, which equals to one in 2008 and zero in 2007, and their interaction term. The dependent variable in column (1) and (2) is computed as the difference in log credit granted by bank  $j$  between year  $t$  and  $t-1$ . Robust standard errors in brackets. \*\*\* coefficient significant at 1 per cent; \*\* at 5 per cent; \* at 10 per cent.

Dep. Variable	growth credit	growth credit
	(1)	(2)
<i>dlocal</i>	-0.201** (0.097)	-0.471* (0.264)
<i>crisis</i>	-0.424*** (0.102)	-0.446*** (0.135)
<i>local*crisis</i>	0.017 (0.126)	0.030 (0.202)
Bank FE	No	Yes
Observations	673	673
Number of banks	348	348

Table 11. Extensive margin of credit –Firms' characteristics

This table reports estimates of the determinants that a lending relationship between firm  $i$  and bank  $j$  that was in place in 2007 was terminated in 2008. Among regressors, we include our main variable of interest,  $dlocal$ , which is a dummy that takes the value of one if the bank's index of localism is above the median and zero otherwise. We then include the interactions between  $dlocal$  and firms' balance sheet characteristics: ROA, leverage, age, EBITDA, rating and size.  $Share\ bank$  is the relative share of credit lent by bank  $j$  to firm  $i$ . Robust standard errors in brackets. \*\*\* coefficient significant at 1 per cent; \*\* at 5 per cent; \* at 10 per cent. Marginal effects displayed.

Dep. Variable	terminate	terminate	terminate	terminate	terminate	terminate	terminate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$dlocal$	-0.064*** (0.011)	-0.007 (0.034)	-0.038 (0.032)	-0.051*** (0.016)	0.004 (0.049)	-0.083*** (0.017)	-0.083*** (0.010)
ROA	-0.002*** (0.001)						
$dlocal*ROA$	0.001 (0.003)						
leverage		0.001*** (0.000)					
$dlocal*leverage$		-0.001** (0.001)					
age			-0.000* (0.000)				
$dlocal*age$			-0.001 (0.001)				
EBITDA				0.0003 (0.0003)			
$dlocal*EBITDA$				-0.002 (0.002)			
rating					0.008*** (0.002)		
$dlocal*rating$					-0.016* (0.010)		
firm size						0.001 (0.006)	
$dlocal*firm\ size$						0.050 (0.042)	
share credit	-0.217*** (0.080)	-0.218*** (0.083)	-0.210*** (0.081)	-0.224*** (0.080)	-0.218*** (0.083)	-0.216*** (0.081)	-1.301*** (0.249)
$dlocal*share\ credit$							1.282*** (0.255)
Observations	15,423	15,423	15,423	15,423	15,423	15,423	15,423

